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# Reliable and Secure Body Fall Detection Algorithm in a Wireless Mesh Network

By

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Science in Computer Engineering

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*Dedicated to my parents, Mr. Rajendra Rakhecha*

*and Mrs. Chanchala Rakhecha*

## **Acknowledgements**

Foremost, I would like to express my sincere gratitude to my primary thesis advisor Dr. Kenneth Hsu for his patience, motivation and constant support and guidance that he extended throughout the duration of this research. His valuable suggestions and useful comments, this work would not have been possible. This thesis owes much of its contents to his ideas and guidance. My sincere thanks to Dr. Amlan Ganguly and Dr. Andres Kwasinski, whose constructive comments and suggestions improved the quality of this dissertation. Special thanks to Sam Skalicky who helped me with coding throughout the research. I have no words to express my gratitude to my family for their endless support and love and my friends for their continued support and encouragement.

## **Abstract**

Falls in elderly is one of the most serious causes of severe injury. Lack in immediate medical help makes these injuries life threatening. An automatic fall detection system, presented in this research, would help reduce the arrival time of medical attention, reduce mortality rate and promote independent living. Therefore, the algorithm finds its application in the medical field, specifically in nursing homes. The system designed and presented in this research is not only capable of detecting human falls but also distinguishing them from routine fall-like activities. Falls are detected with the help of a small wearable embedded device, i.e. Texas Instruments' eZ430 Chronos watch which is wireless development kit. The watch operates at an RF frequency of 915MHz to communicate with each other in a wireless network.

The wearable wrist watch is programmable and has an in-built accelerometer sensor and microcontroller circuitry. The accelerometer sensor is motion sensitive and measures the acceleration due to gravity. Whenever a fall is detected the watch sends a signal to the neighboring watch, which is always in the monitoring mode. Signal transmission and reception between these devices is via wireless communication, where every node is a sensor forwarding the signal to the next node. A wireless mesh network helps in quick transmission of signals thereby alerting the authorities.

In order to differentiate between body fall and Activities of Daily Life, various body motions and gestures have been studied and presented. The features of a real fall and that of normal human motions are extracted and analyzed from the data obtained by volunteers who participated in the research. Evaluation of results led to setting forth threshold values for parameters like acceleration, change in co-ordinate axes and angle of orientation. Over-passing the threshold raises a fall alarm to bring to the attention of the hospital authority.

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## Chapter 1 Introduction

A fall is defined as “unintentionally coming to ground, or some lower level not as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure”. [1] Approximately 3% of all fallers lie for more than 20 minutes without external support. [2] The need of assistance in the case of unconsciousness or extreme injury is the main reasons why elders leave the comfort and privacy of their own home to live in an assisted-care environment (40% of nursing home admissions are due to falls). [1] Thirty-two percent of elderly people aged over 75 years have ever fallen at least once a year, and among them, 24% have seriously injured. [1] In the recent years the number of fall detection systems has increased but very little work has been done for the same in the wireless domain. Body attached accelerometers and gyroscopes are used for detecting human motions and falls. This design presented in this research uses body mounted embedded System on Chip (SoC) device with in-built accelerometer and micro-controller circuitry to distinguish between Activities of Daily Life (ADL) and a genuine fall so as to avoid triggering false alarms. The fall detection algorithm takes into account the parameters like acceleration due to gravity and the co-ordinate reference points for fall detection. The detected fall triggers a mechanism to alert the authority via other sensor nodes. The signal wirelessly reaches the destination node in minimum number of hops. The minimum range of communication between a sender and a receiver node is 1meter. The range may be increased by introducing additional sensors in the path.

## 1.1. TI Chronos eZ430 Watch Setup

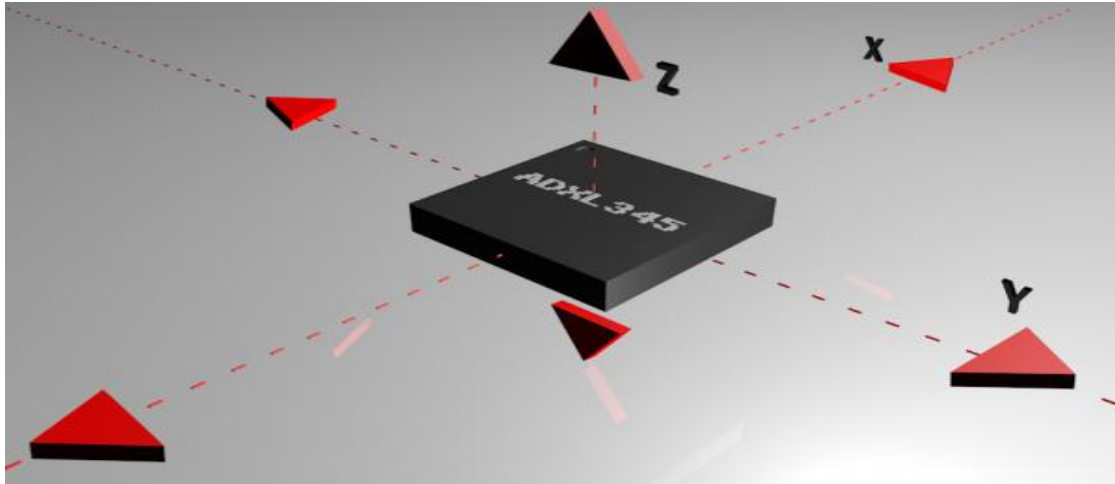
Texas Instruments' eZ430 development kit is used for the study and implementation of the body fall detection algorithm. The eZ430-Chronos software development tool is a highly integrated, wearable, wireless and embedded development system in the form of a wrist watch that is based on the CC430F6137 microcontroller. The CC430F6137 family of micro-controller comes with an embedded transceiver which operates at a frequency of 915MHz. It is a sub-1 GHz RF System on Chip which has a 96 segment LCD display. The display makes the system highly user interactive. Along with the display and the micro-controller, it comes with a pressure sensor and a 3 axis accelerometer sensor for motion sensitive control. The algorithm is implemented in a wireless sensor network. The integrated wireless interface allows the eZ430-Chronos to act as a central hub for nearby wireless sensors. This feature is utilized in implementing the application of fall detection by sending the signal over to the neighboring nodes/watches worn by the nurses. The eZ430-Chronos watch may be disassembled to be reprogrammed with custom applications and includes an eZ430 USB programming interface. Integrated development environment used for this research is the Code Composer Studio and the programming language used is "C". The watch is programmed with the help of an additional USB emulator which connects to the PC/laptop for real time and In-System Programming.



Figure 1.1: (a) Watch module attached to debugger (b) eZ430 Chronos watch with USB emulator

## 1.2.Accelerometer

Accelerometer is an electro-mechanical device that measures the static and dynamic forces of acceleration. Static force is measurement of acceleration due to gravity whereas dynamic forces include the vibrations or any kind of movement. Acceleration is rate of change of velocity measured in  $\text{m/s}^2$ . Accelerometers measure acceleration in either be one, two or three axes.



**Figure 1.2: Axes of measurement for a triple axis accelerometer**

Figure 1.2 shows a tri-axial accelerometer. Tri-axial accelerometers are more widely used given their accurate measurements. Tri axial accelerometer measure the acceleration in xyz axes and are more accurate than the single or bi-axial devices. Accelerometers come in a wide range of specifications. These ranges vary from  $\pm 1g$  to  $\pm 250g$ .  $+1g$  refers to the gravitational acceleration which is  $9.8\text{m/s}^2$ . These specifications may be in terms of sensitivity and selectable range of forces that it may measure. Smaller the range of accelerometer, higher is the sensitivity.

Accelerometers may be capacitive or based on piezo-electric materials. Capacitive accelerometers contain and internal capacitive plates, some of these are fixed, while others are attached to very tiny springs that move internally as acceleration forces act upon the sensor. As these plates move, the capacitance between them changes. The change in the capacitance helps in determining the acceleration. Other

accelerometers can be centered on piezoelectric materials. They are basically used to measure dynamic changes in any mechanical quantity. These tiny crystal structures output electrical charge when placed under mechanical stress. The accelerometer used for this research is a BMA 250- capacitive tri-axial accelerometer and the selected range is  $\pm 4g$ .

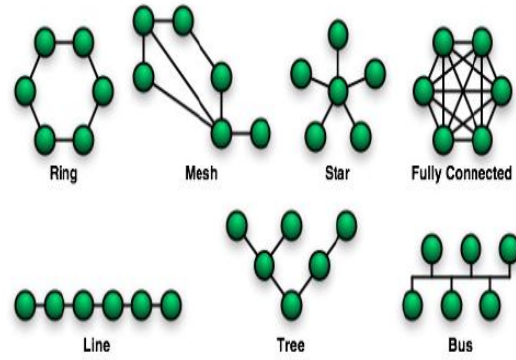
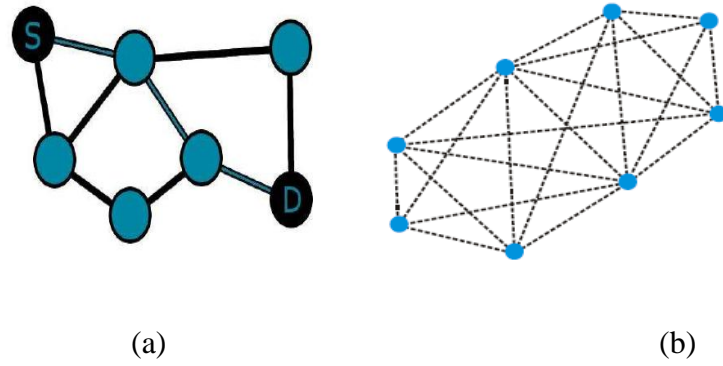
Accelerometers find their applications in the industrial field as the measure dynamic changes like shock, acceleration and vibration. They are also used for gaming, medical monitoring, compass, seismographs etc.



**Figure 1.3: Accelerometer functions**

### **1.3.Wireless Mesh Network**

Wireless communication provides unprecedented freedom and mobility for a growing number of devices. Wireless network eliminates laborious task of wiring as these devices need no wires to stay connected. Wireless network facilitates easy, reliable and secure data transfer over long or short distance. Mesh is a network topology where devices are inter-connected via many links to forward the traffic flow [3].

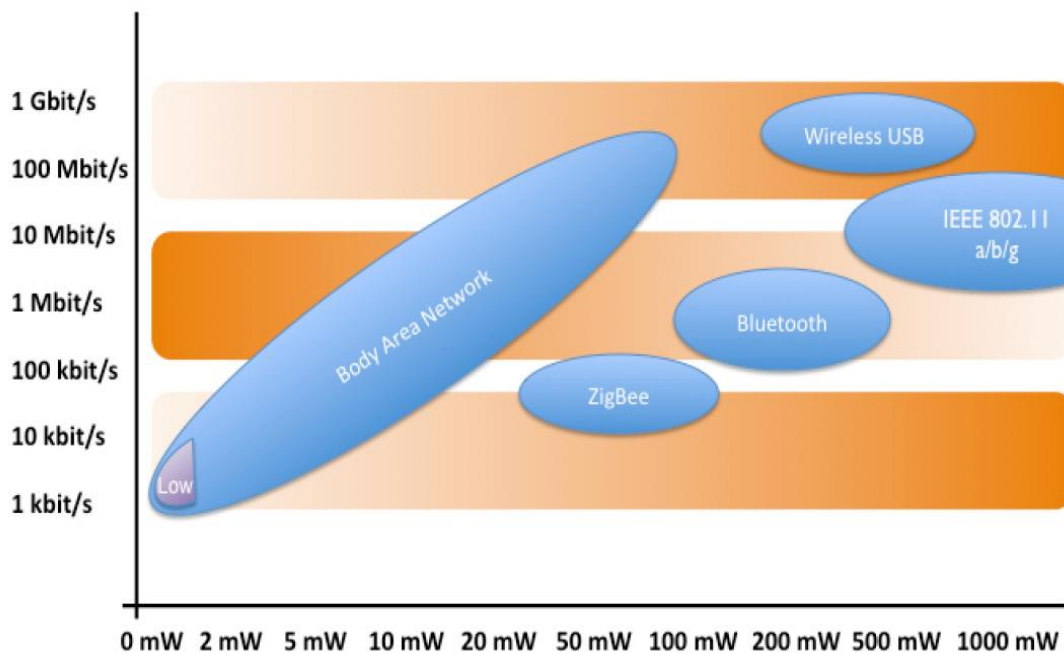


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**Figure 1.4: (a) Wireless mesh network with source S and destination D (b) Wireless mesh network with intermediate nodes [3]**

#### ©Body area network

A Body Area Network is formally defined by IEEE 802.15 as, “a communication standard optimized for low power devices and operation on, in or around the human body (but not limited to humans) to serve a variety of applications including medical, consumer electronics / personal entertainment and other” [4]. Novel technology enhancements, constant miniaturization of sensor devices and wide applications of wireless network has made Wireless Body Area Network (WBAN) very popular in the field of healthcare. In WBANs, sensors are used to measure and/or monitor various human activities such as heart beat, body movement, temperature, etc by placing them on the body of the patient or by implanting them [5].



**Figure 1.5: Data rate Vs. Power for BANs [4]**

Figure 1.5 shows a graph between the power consumption and data rates for Body Area Networks. It is seen that BAN occupies majority of the graph as compared to other protocols such as Zigbee, Bluetooth and wireless USB. It can also be seen that BAN accounts for the lowest power consumption in spite of having a larger range of data rates. Therefore, most of the medical applications use BANs for its ultra low power consumption, ease of data transfer and higher data rate.

Distance	2 meter – Standard
Network Density	2-4 nets/m <sup>2</sup>
Network Size	Maximum: 100 devices/ network
Power consumption	1mW/Mbps
Startup time	<100uS
Latency (end to end)	10mS
Network Setup time	<1 sec

**Table 1 BAN specification [4]**



Table 1 shows basic features of a Body Area Network. BANs have higher bandwidth, more scalability, less start up time and good coverage in terms of range of communication.

### **1.3.1. Wireless Sensor Network**

A multi hop network in which stationery routers relay traffic on behalf of other routers or client station wirelessly is known as a Wireless Mesh Network (WMN) [6]. Mesh is a network topology where devices are connected via many links and select the optimal path to forward traffic [7]. In a sensor network, data collection is related to the connectivity between the sensor nodes and the coverage. In this research, data is collected from the sensor nodes and forwarded to the receiving node which may be thought of as the base station. Relaying data to the data sink is uniform in nature and relieves other sensor nodes from getting overburdened with data. The type of communication in the network is simplex and only one way. The receiver nodes receive the data but will not transmit and vice versa.

Lifetime is the most critical issue for sensor networks as most of them work on battery powered nodes and energy consumption is extremely high. However, researchers suggest that energy consumption could be reduced by considering the interdependencies between individual layers in the network protocol stack. Also, using a low power model for transmission and forwarding the packets will help mitigate power losses, lower energy consumption and improve the lifetime of the network. Sensor networks are found to interest most of the monitoring fields like surveillance, warfare, medical applications, micro-surgery and environmental monitoring [8]

## **1.4.Zigbee**

In a wireless sensor network, the communication method varies depending on the application either at the medical, industrial or scientific. One of the most widely used communication protocols is the ZigBee protocol, which is a technology composed of a set of specifications designed for wireless sensor networks. This system is characterized by the conditional type of communication, its mean, which not 20 require a

high volume of information (just over a few kilobits per second) and also have a limited walking distance. ZigBee, also known as IEEE 802.15.4, can operate at three different frequency bands. Freescale module presented in section 3.5 uses the Zigbee protocol for data transfer and to communicate with the controller unit. ZigBee is a low-cost, low-power, wireless mesh network standard. Zigbee is widely deployed in wireless control and monitoring applications due to its low cost. The Ultra low power feature not only allows longer battery life but also improves the reliability and the range.

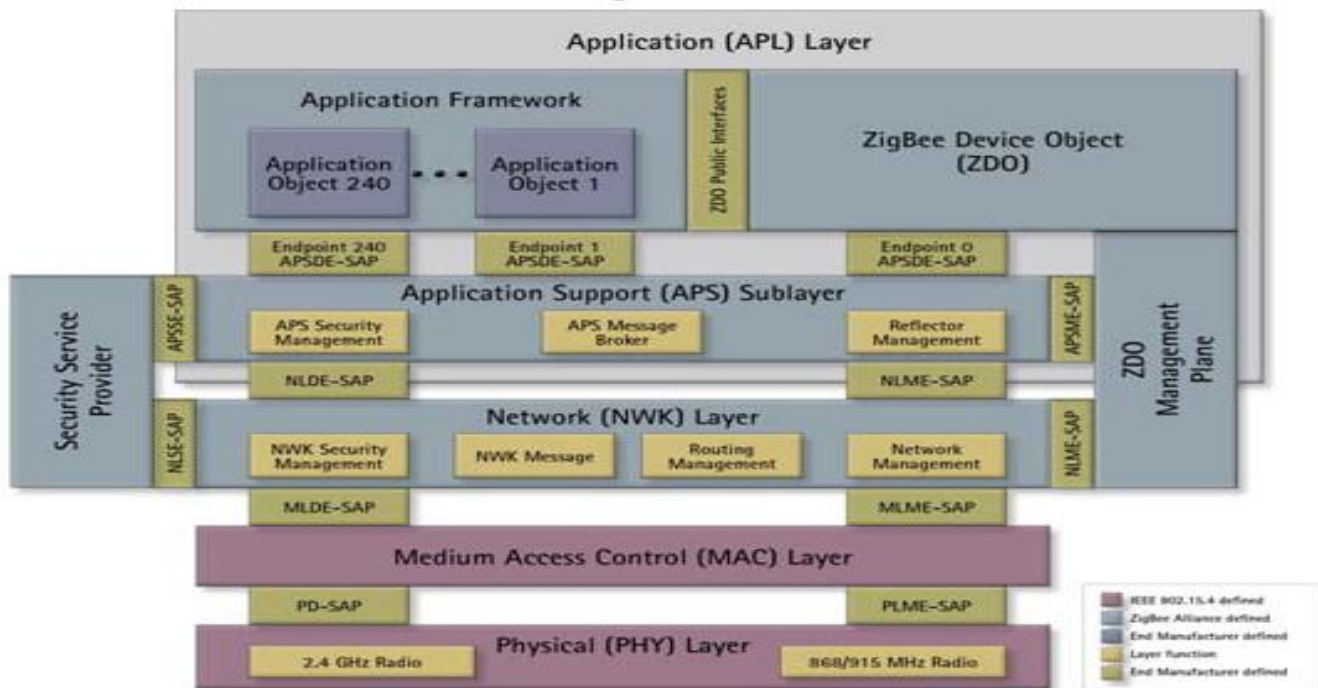


Figure 1.6: Zigbee protocol stack [9]

For sensor network applications, key design requirements revolve around long battery life, low cost, small footprint, and mesh networking to support communication between large numbers of devices in an interoperable and multi-application environment. ZigBee is targeted at applications that require a low data rate and long battery life. ZigBee has a data rate of 250 Kbit/s, which is best suited for periodic or intermittent data transmission from a sensor or input device. The technology defined by the ZigBee specification is intended to be simpler and less expensive than other WPANs, such as Bluetooth [9].

## 1.5.Fall Detection

Fall is one of the most serious causes of fatal injuries amongst the elderly population. Most of the prevalent fall detection systems fail to distinguish between Activities of Daily Life (ADL) and a real fall. In this research, the system developed successfully identifies a genuine fall and also distinguishes it from fall like activities like sudden movement. Texas Instrument's eZ430 Chronos embedded watch system with a built-in accelerometer. Primary objective of this research is to reduce the mortality rate occurring due to elderly falls and to promote independent living.

Parameters such as acceleration, angle of orientation, angle of tilt and reference points in 3D co-ordinate space has been considered. Threshold limits have been set for all these parameters, crossing of which will result in setting of an alarm. Following sections present a detailed approach and explanation with regards to the design of the algorithm, statistical analysis and the implementation.

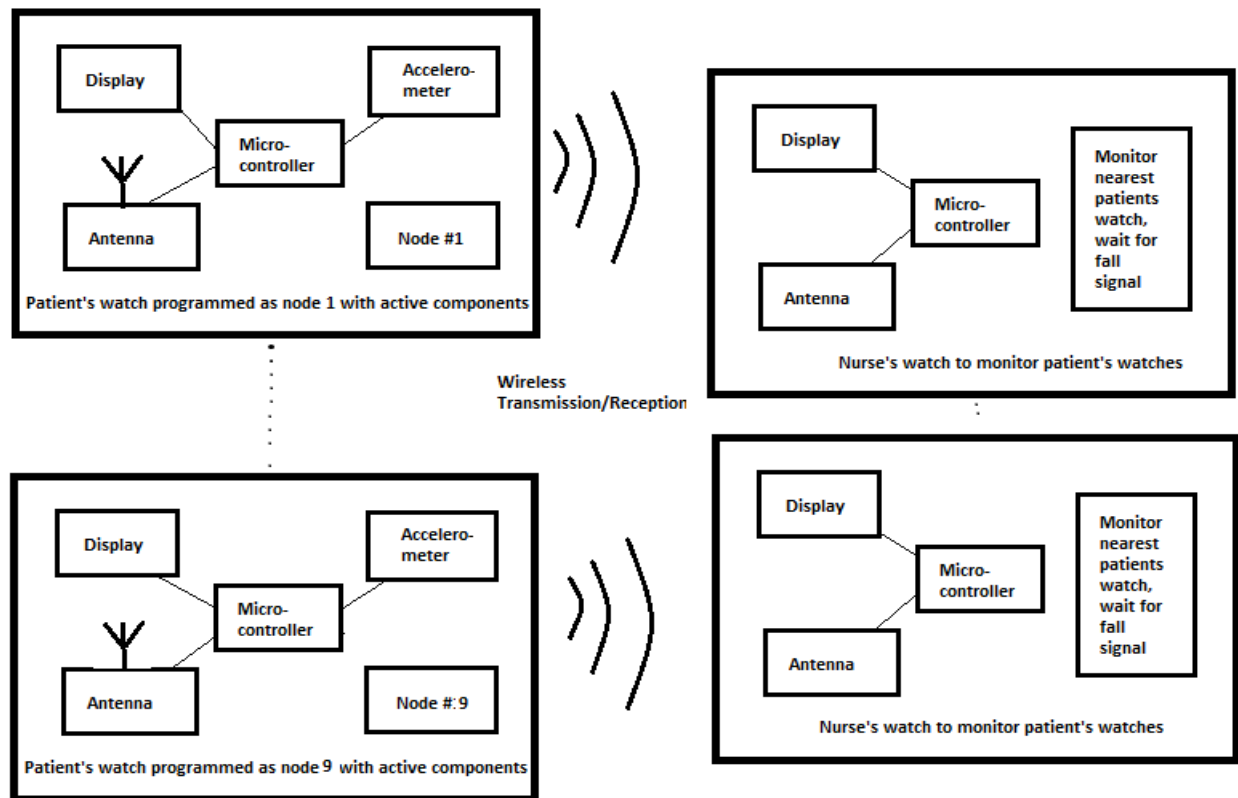


Figure 1.7: Block diagram of fall detection system

## Chapter 2 Related Work

Several research and computing projects have successfully detected and distinguished daily activities by attaching accelerometers in known positions. [10] The work proposed in [10] uses the accelerometer to determine various movements of body without knowing the orientation. It makes use of the co-ordinate system which acts as the axes of the accelerometer. In the work presented, gravity component on each axis is averaged over a specific sampling frequency. From these acceleration values, vertical acceleration is calculated and the final difference between the corresponding acceleration and the vertical acceleration values gives the accurate reading. Fall detection mechanism and methodology is presented in [11], [12] [13] and [14].

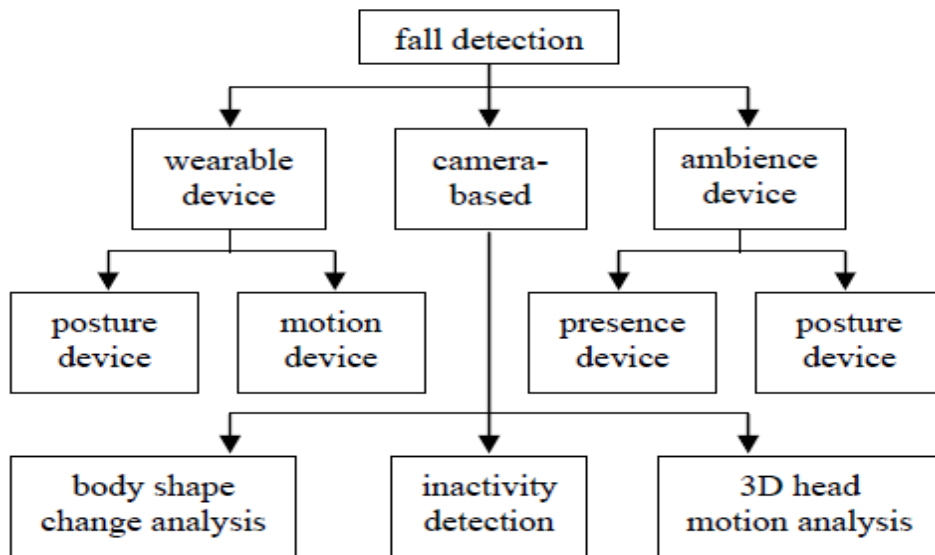


Figure 2.1: Hierarchy of approaches and classes of fall detection methods [7].

Fall detections systems may be categorized into three types. Figure 2.1 shows three different categories of prevalent research on fall detection. This research is motivated from the first type of system i.e. wearable device. The first is using a wearable sensor device which triggers an alarm. The second approach is by constant monitoring using a live camera and third is using an ambience device which uses multiple sensors and collects relevant data. The ubiquitous fall detection systems lack automatic recognition and

hence, the patient is left in fallen state until help reaches him. The present systems also make use of accelerometer sensors for motion detection. Many devices also take into consideration the altitude along with the change in acceleration for accuracy. Bluetooth and Zigbee is a common mode of communication for these devices.

The research presented in D. Chen et al. [1] uses a micro-controller circuitry and a data-logger for collecting and processing the data. The processed data is sent over to the monitoring centre through Zigbee gateway and detects if a fall has occurred or not. Similar model was showcased A. Sorvala in [15]. The team made use of a gyroscope along with accelerometer sensor to set two threshold limits for detecting fall. This led to higher accuracy as the gyroscope used also measured the angular velocity and angle of tilt. M Silva and et al [16] used mobile with in-built accelerometer and developed an Android based application to monitor human motion and detect body fall. The application was programmed to calculate the time lapse between the “pre-fall” position and the “free-fall” or “real fall” positions. If the time difference and the change in acceleration due to gravity were found to be higher than the set threshold, an email or message would be sent to the pre-defined contact saved in the mobile device. A. Bourke and et al in [13] used the Bluetooth technology to send the fall signal from the device to the emergency contact. The algorithm is not implemented in wireless network but the waist mounted embedded fall detection device transmits data to the nearest Bluetooth device on one-on-one basis. They have also presented the change in values for different daily life activities and compared it with the real fall.

## Chapter 3 Methodology and Algorithm Design

In order to successfully implement the fall detection algorithm, it is first important to differentiate and understand the basic difference between a real fall and fall-like activities. Fall-like activities are regular activities that a person does in everyday life like walking, jogging, standing quickly, lying down, jumping etc. All these activities are similar to fall except that the change in acceleration is not same. The daily life activities are tested and different parameters like acceleration due to gravity, change in the co-ordinates in three axis, angle of orientation and angle of tilt are measured and analyzed. All these parameters are then compared with that of the real fall to correctly define a fall signal. Analysis and calculations presented in the sections below clearly show that the difference in change of acceleration for regular activities is extremely small as compared to that of a real fall. The most significant parameter is the change of acceleration in the Z axis. It is observed that whenever the watch is dropped in the vertical direction, maximum change occurs in the acceleration in the z axis. Therefore, the change in the  $A_z$  component of acceleration is the highest. Setting a threshold limit on  $A_z$  and the total acceleration led to the precise calculation of the fall signal. The algorithm for body fall detection takes into account the values obtained from the accelerometer and the changes in the co-ordinate axes. The tri-axial accelerometer in the watch measures the acceleration due to gravity in the x, y and z axes. The single axis change in acceleration ( $A_z$ ) works significantly in determining a real fall. The formula mentioned below makes use of this phenomenon to distinguish between a genuine body fall and ADL. The data obtained from the accelerometer is processed at real time to avoid time lapses.

Different ADL and body fall scenarios have been studied and identified to characterize and specify differences between them. It not only helps in developing a new algorithm but also helps in improving existing designs. 6 different ADL are characterized depending on the body movement. Similarly 4 different fall positions are considered. The characteristics are mentioned below:

1. Forward fall: Ends up lying in a flat position. The body position remains lateral to ground if fell on knees and unable to recover. Time of fall may last from 1 to 2 seconds.
2. Backward fall: Most severe type of fall. Body position remains lateral. Change in acceleration is maximum and may cause serious head injury. Fall time may be 1 to 2 seconds
3. Fall to the left: Higher probability of recovering from the fall. Higher chances of triggering a false alarm due to orientation change.
4. Fall to the right: Higher probability of recovering from the fall. Higher chances of triggering a false alarm due to orientation change.
5. Fall from bed: Fall altitude is less. Injury may depend if the person fell on ground or mattress.
6. Fall from a chair: Fall height is slightly higher. Time of fall varies from 1 to 2 seconds.

### 3.1. Approach

The fully reprogrammable development kit is based on the CC430F6137. The CC430 is an MSP430 that has an integrated <1GHz wireless transceiver for custom wireless applications. Along with the accelerometer, a pressure sensor, temperature sensor and voltage battery monitor is also embedded in the watch. The watch has a 96 segment LCD display drive directly by the CC430. Integrated development environment used for this research is the Code Composer Studio and the programming language used is “C”. The watch is programmed with the help of an additional USB emulator which connects to the PC/laptop for real time and In-System Programming. After the watch is programmed, the side buttons on the watch are used for navigating through the menu and selecting the desired option from it. The Menu consists of 5 options:

- i) **Idle:** This is similar to reset condition. If the watch is not transmitting or receiving any data, it stays in the idle state. Power consumption of the watch in “idle” mode is the least. Also, after successful fall detection, the watch needs to be brought out of the radio mode and set to idle mode again.

- ii) **Node Address:** This option allows the user to set patient's node to a unique single digit node address. Each node number represents the patient. The network can have maximum up to 9 patients with their watch ready to transmit fall signal. On discovering a fall, this node address is displayed on the receiver node worn by the nurse.
- iii) **Transmit start:** The patient's watch needs to be in "transmit" mode for fall to be detected. This mode activates the radio module of the watch and also activates the accelerometer. Power consumption is the highest as the accelerometer and radio device both are functioning together.
- iv) **View node:** "View node" menu option is for the nurse's watch. The selected node number is continuously monitored for fall. The watch is capable of monitoring multiple nodes and detects more than one fall.
- v) **Battery Voltage:** Shows the battery life and notifies if the battery needs to be replaced. The voltage of a new battery is 3V and may function up to when it reaches 1.2 V.

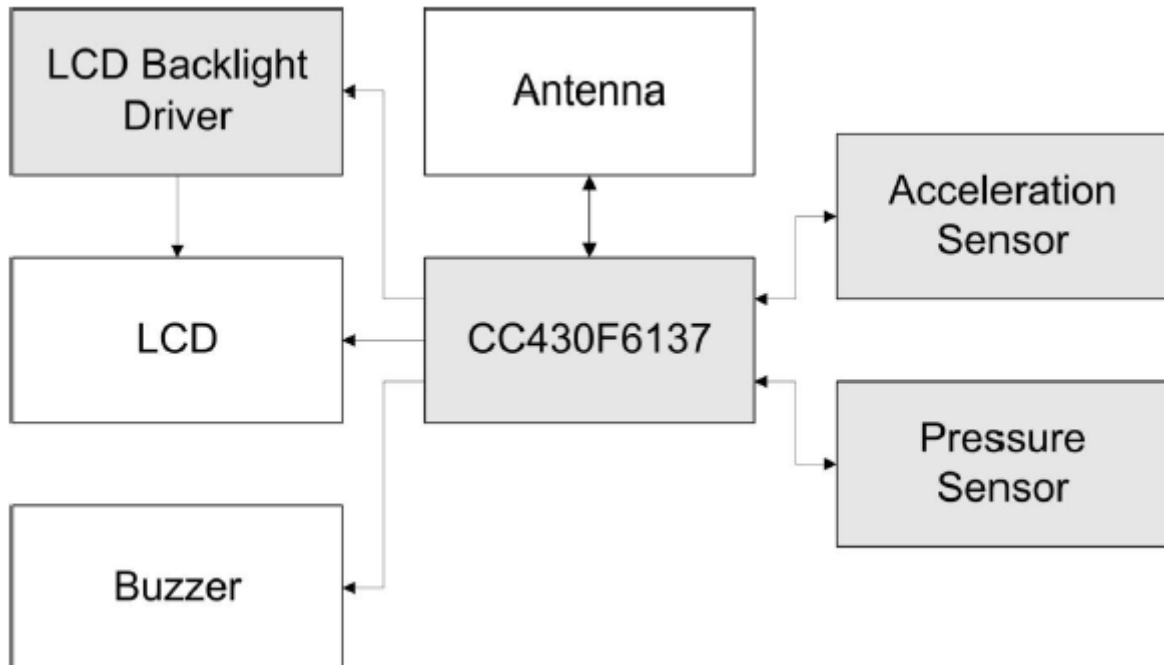
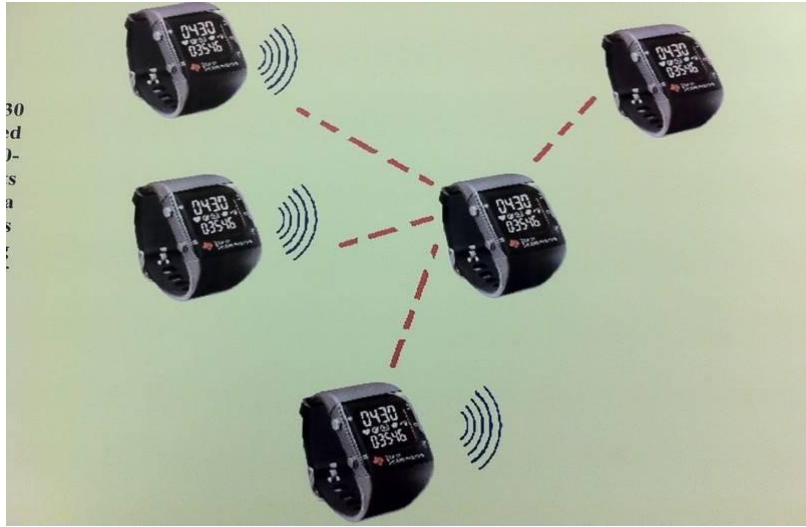


Figure 3.1: eZ chronos watch block diagram



Figure 3.1 shows the basic block diagram of the Chronos watch module. It shows a micro-controller unit which acts as the driving block for the Display, buzzer, antenna and the acceleration sensor or accelerometer. In this research due to the simultaneous operation of the display, antenna and the acceleration sensor, the buzzer cannot be triggered due to the very high energy consumption by the antenna in the radio mode.



**Figure 3.2: Chronos watch in transmit and receive mode**

Figure 3.2 shows basic diagram of the implemented algorithm. It can be seen that the watch in the center is transmitting data to the other watches which are receiving the data. The transmitting node represents the patient whereas the receiving nodes are the nurses or any hospital staff. The actual implemented design may have up to 9 transmitting nodes. The number of receiving nodes may vary from 5 to 9. A single receiver node is capable of monitoring all 9 transmitter sensors but to avoid over burdening, the number of receiver nodes are considered to be half of transmitter nodes. As mentioned earlier, communication and information relaying throughout the network follows simplex type of communication.

Five student volunteers wore the watch to test the correctness of the algorithm and observe different patterns of daily activities and falls. The watch worn by the patient is set to single digit number i.e. node number and no two watch can have the same node number. All these watches are always set in the “transmit” mode with an accelerometer in active state. The accelerometer keeps collecting data at real time

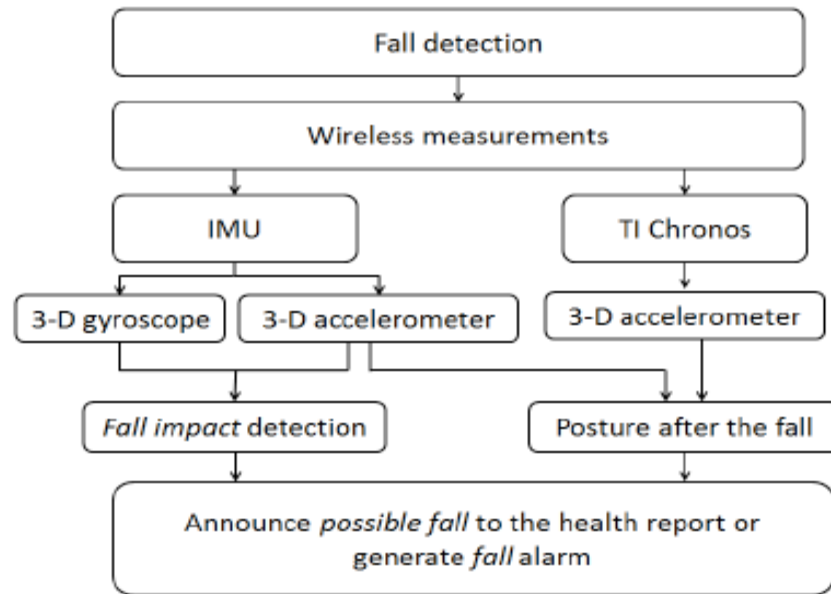
until a real fall is detected. The watches worn by the hospital authorities or nurses are in the “monitor/receive” mode. If a patient falls, an alert signal is broadcasted across the wireless nodes. This signal reaches all the neighboring sensor nodes which are constantly in the “monitor” mode. The display of the watches shows the node number of the patient who fell and needs assistance. Once the authority reaches the patient, the transmission is stopped manually using the reset button present on the watch. The signal reaches the nurse watches via intermediate watches in minimum number of hops. The intermediate watches may not be worn and be used only for the purpose of increasing the radius of the network. The range of the signal may be further extended by introducing additional watches in the path. This embedded system adds excellent features to the ubiquitous devices in health care. The features are:

- i. Distinguishes between real fall and daily life activities like jumping or sudden jolt.
- ii. Reliable and protected transmission of signal in wireless network when a real fall is detected.
- iii. Hands free device which automatically alarms the authority on the detection of fall. It does not require the patient to activate the device on falling.
- iv. The algorithm is secure in nature as no other device may intercept the radio transmission or disturb it in any way.
- v. The algorithm is highly reliable as most of the significant parameters such as co-ordinates reference points, acceleration, angle of orientation and Tilt angle has been considered

### **3.2.Fall Detection Algorithm**

The in-built accelerometer plays the most significant role in the accomplishment of the body fall detection algorithm. The entire algorithm revolves around the readings measured by the accelerometer and the threshold values. Accelerometer is a motion sensitive electro-mechanical device which measures the acceleration due to gravity. The algorithm follows the following 2 important steps:

- 1) Calculation of the acceleration values in x, y and z co-ordinate axes, calculating the overall acceleration value and comparing it with the threshold value.
- 2) If the value of the calculated acceleration is found to be greater than the threshold value, fall flag is raised and alert signal transmitted across the wireless network, if not, the accelerometer continues its normal mode of operation until a genuine fall is detected.



**Figure 3.3 fall detection system [15]**

Figure 3.3 shows a fall detection system which follows almost similar approach as presented in this thesis. The system uses wireless communication for data transmission, not in a mesh network. The Inertial Measurement Unit (IMU) consists of an acceleration sensor and a gyroscope for estimating the impact of fall. TI chromos module is used for determining the posture after the fall. The Impact of the fall can be determined by computing the total change in acceleration force with respect to Earth's gravitational pull. Similarly, posture determination is done by calculating the angle of orientation.

### 3.3.Statistical Analysis

To consider the acceleration uniformly, data change the three axes can be taken, which is the magnitude of acceleration in three-dimensional space when the three acceleration values are for the same point in time. The TI Chronos circuitry processes these samples sequentially but fast enough to estimate the total change in acceleration. The value is calculated at the rate that the accelerometers are sampled and when it exceeds a threshold then it is safe to say that a fall has occurred. The threshold can be set based on the results obtained from fall and non-fall activities. The lowest change in acceleration measured for fall is about three times “g”. It is also confirmed that the acceleration does not exceed 3g for daily activities. However, for a rigorous movement or sudden jolt, the value may rise and equal 3g. Due to the overlap of ranges for fall-like and fall scenarios, it is extremely important to set another threshold limit to validate and correctly detect fall. The following formulas give an exact idea about the implementation of the fall detection algorithm.

$$A_{total} = \sqrt{(Ax^2) + (Ay^2) + (Az^2)} \quad 3.1$$

$$\omega_{Tot} = \sqrt{(\omega x)^2 + (\omega y)^2 + (\omega z)^2} \quad 3.2$$

In equation 3.1,  $A_{total}$  is the total sum vector magnitude for the 3-D acceleration data and  $\omega_{Tot}$  is the angular movement where  $Ax$ ,  $Ay$ , and  $Az$  denote accelerations whereas  $\omega x$ ,  $\omega y$  and  $\omega z$  is the angular velocity along x, y and z-axis [1]. The threshold value is set using Eg.  $A_{total} = \sqrt{(Ax^2) + (Ay^2) + (Az^2)}$

3.1, if the acceleration was more than 3g in the z axis, fall flag would be raised to alert the authorities. Also if  $\sqrt{Az^2} > \sqrt{Ax^2 + Ay^2}$ , severe category fall is detected. The comparison with the acceleration in the  $Az$  component is used as a second threshold.

In the absence of actual acceleration with respect to the ground, the accelerometers detect the normal force of gravity, 1 G, directed upward from the ground [15]. This force is always present and is a static component in the acceleration data. Whenever the patient is in stationery position, the force is equivalent to 1g and reflects the normal force. When a person falls, he or she undergoes a large change in position from

before the fall to after. The simplest example would be from standing upright to lying flat, an orientation change in the mote of 90 degrees. The actual change in orientation may be more or less than that, depending on the initial and final position of the person, but in any case, there is usually such a change, except for special cases like when a person rolls off the bed. From the orientation information, such an angle of change can be estimated using the dot product of the acceleration vectors before a fall and after.

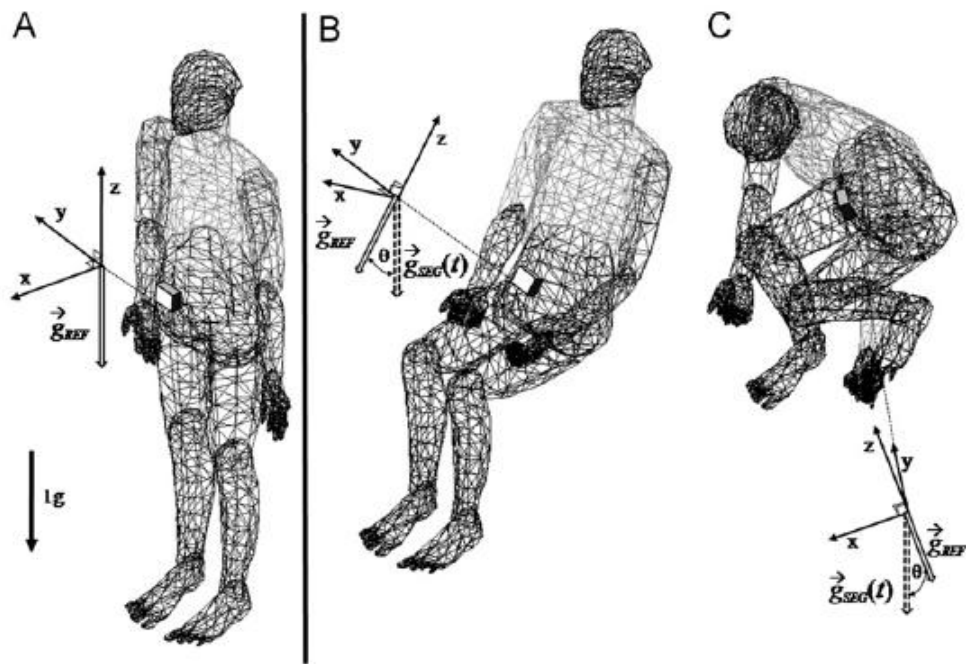


Figure 3.4: The figure shows the orientation and calculation of angle of inclination [1]

Figure 3.4: The figure shows the orientation and calculation of angle of inclination [1]Figure 3.4: The figure shows the orientation and calculation of angle of inclination [1] shows different body orientation and the change in the value of the acceleration, co-ordinates and the angle of orientation between them. The first position shows a standing model of a human being where the acceleration due to gravity is only the single component acting vertically downward towards the direction of earth. Three components of acceleration have a value which exactly equals the Earth's acceleration due to gravity i.e.  $9.8\text{m/s}^2$ . The second model of the figure is in sitting position due to which the other components of acceleration also come into picture. It is seen that the y axis of acceleration develops and angle theta with the normal and the

z axis. The angle also brings tilt angle into calculation which aids in achieving accuracy. The third model shows a different human movement where the angle is formed between the y axes. These angle formation and analysis of angle of tilt is performed for daily activities to differentiate their characteristic results from a genuine fall. The values obtained from the daily activities and that of fall vary in very high magnitude as fall happens with greater force, impact and the change in the angle formation along with the tilt is very sudden. However, for some fall-like activities, also have certain characteristics which are exactly same as that of a genuine fall. It can lead to give incorrect results and set off a false alarm if a sudden activity is wrongly identified as a fall. So as to avoid false triggering of alarm, the data is processed and analyzed for its acceleration and change in angle of orientation along with co-ordinates. Body movement or activity may be categorized as ADL if the differences between the analyzed values are small; else they are categorized as fall.

The second aspect of the algorithm is the determination of the angle of tilt or tilt angle and angle of orientation. The measurement of angle of orientation is an essential component in determining a fall. It helps in determining the exact position of the patient before fall and also how severe or amenable the fall was. The angle of orientation is calculated as follows:

$$\Theta_{\text{orientation}} = \arccos(A_z / (\sqrt{A_x^2 + A_y^2 + A_z^2})) \quad 3.3$$

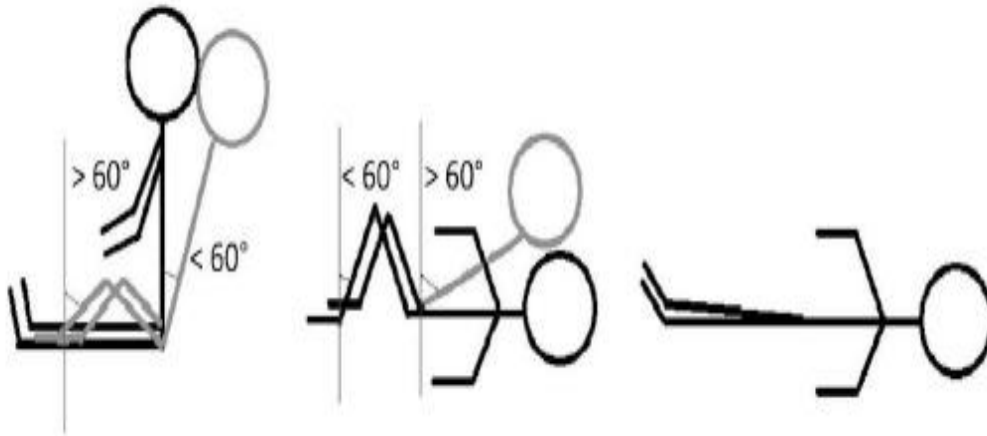
Where  $A_x$ ,  $A_y$ ,  $A_z$  are the accelerometer values in 3D space co-ordinates [17]. The Tilt Angle TA describes the body's posture, when the body is static. Its value was defined as indicated in Eq 3.4, 3.5, 3.6 below:

$$TA_x = \arccos\left(\frac{A_x}{G}\right) \cdot \left(\frac{180}{\pi}\right) \quad 3.4$$

$$TA_y = \arccos\left(\frac{A_y}{G}\right) \cdot \left(\frac{180}{\pi}\right) \quad 3.5$$

$$TA_z = \arccos\left(\frac{A_z}{G}\right) \cdot \left(\frac{180}{\pi}\right) \quad 3.6$$

Where  $G$  is gravity acceleration ( $=1g$ ). As the sensor position of a standing user, the value of  $TA_x$ ,  $TA_y$ , and  $TA_z$  are  $90^\circ$ ,  $90^\circ$ , and  $0^\circ$ , respectively [11].



**Figure 3.5: Fall positions and angles**

Figure 3.4 is similar to Figure 3.5, the only difference is the absence of the acceleration parameter. For precise detection of fall, a virtual gyroscope is also used for the research. A virtual gyroscope helps in determining the exact position and angle of the person. As the Chronos watch lacks a gyroscope, I-phone applications like “Axelrom”, “iGyro” and “Gyroscope” are used. The Applications can be downloaded from the AppStore. It can be imagined that the I-phone is an embedded device attached to the waist of the patient and the data logger in the applications sends a complete report of the change in orientation via email. From the change in the values obtained from data logger report, angle of orientation can be estimated and it can be safely said that sudden change in values account for fall.

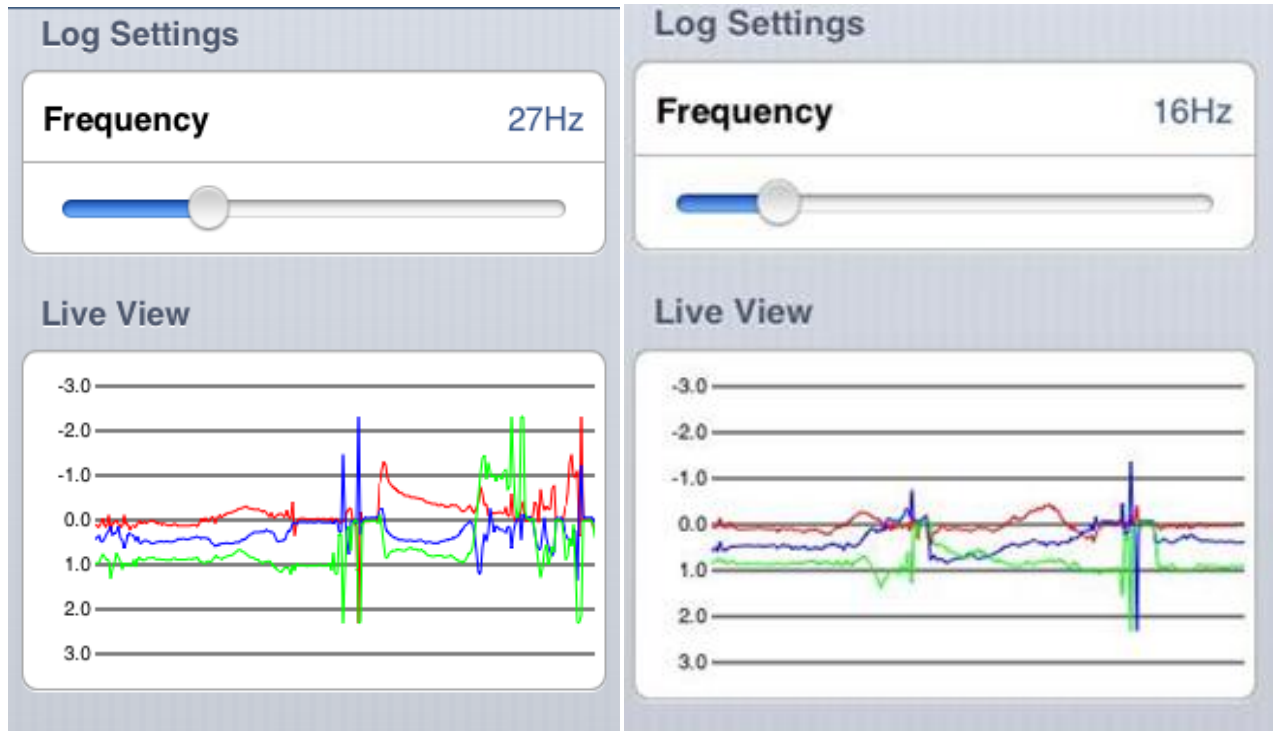


Figure 3.6: I Phone app "data logger "showing acceleration value at different sampling frequency

Figure 3.6 shows the I phone applications used for the purpose of finding acceleration and the angle of orientation. The sampling frequency is varied from 27Hz to 16Hz depending on the position of the person. It can be see that at some time interval the change in acceleration is extremely abrupt and higher than the normal, this account for body fall. Sudden change in Z axes of the acceleration component when the sampling frequency is higher confirms the fall. If the acceleration changes are very high but the change in Az is not more than the set threshold, the activity is normal human movement.

This algorithm extracts features of falls by wireless communication by discriminating between genuine falls and ADL events. The change in acceleration describes the activity level of the body, which contains both the dynamic acceleration and the gravity acceleration.

The following algorithm was used as reference and modified for accuracy, correctness and scalability:

- i. If  $|\alpha_{Amax} - \alpha_{Amin}| < 0.4g$  | and  $|\omega_{Amax} - \omega_{Amin}| < 60^\circ/s$  then
- ii. Recognize the presence of static posture



- iii. Determine the transition before the present lying posture is intentional
- iv. If  $\alpha_{Amax} - \alpha_{Amin} > \alpha_{threshold}$ , detect a fall then return yes

Else return No. [18]

It is modified accordingly to co-ordinate reference system, acceleration, tilt angle and angle of orientation. A threshold value for the acceleration is set for standing and lying body positions. The device needs to be set in the particular mode to monitor the change in threshold values of acceleration due to gravity, orientation or co-ordinates. A fall is detected when acceleration due to gravity changes by thrice the actual acceleration.

The time between the changes in the values of the parameters to be measured also plays in detecting a fall and differentiating it from ADL. Generally, a fall lasts for 1-2 seconds. So the difference in the values at the start and a few seconds after the fall determines if a fall has been detected or not. However, in this research, the time has not been considered as the data is processed at real time and a buffer for keeping the time count is not used. For reliable operation of the fall detection system, genuine fall events should not be missed while sudden body activity and jerks should be minimized. This is taken care by the algorithm as the magnitudes of acceleration in falling are generally greater than those in normal activity [19]. Setting thresholds for each of the three axes of measurement does not work well, because it does not cover all the possible directions of impact in a uniform way. [20] To consider the acceleration uniformly, the norm of the three axes can be taken, which is the magnitude of acceleration in three-dimensional space when the three acceleration values are for the same point in time.

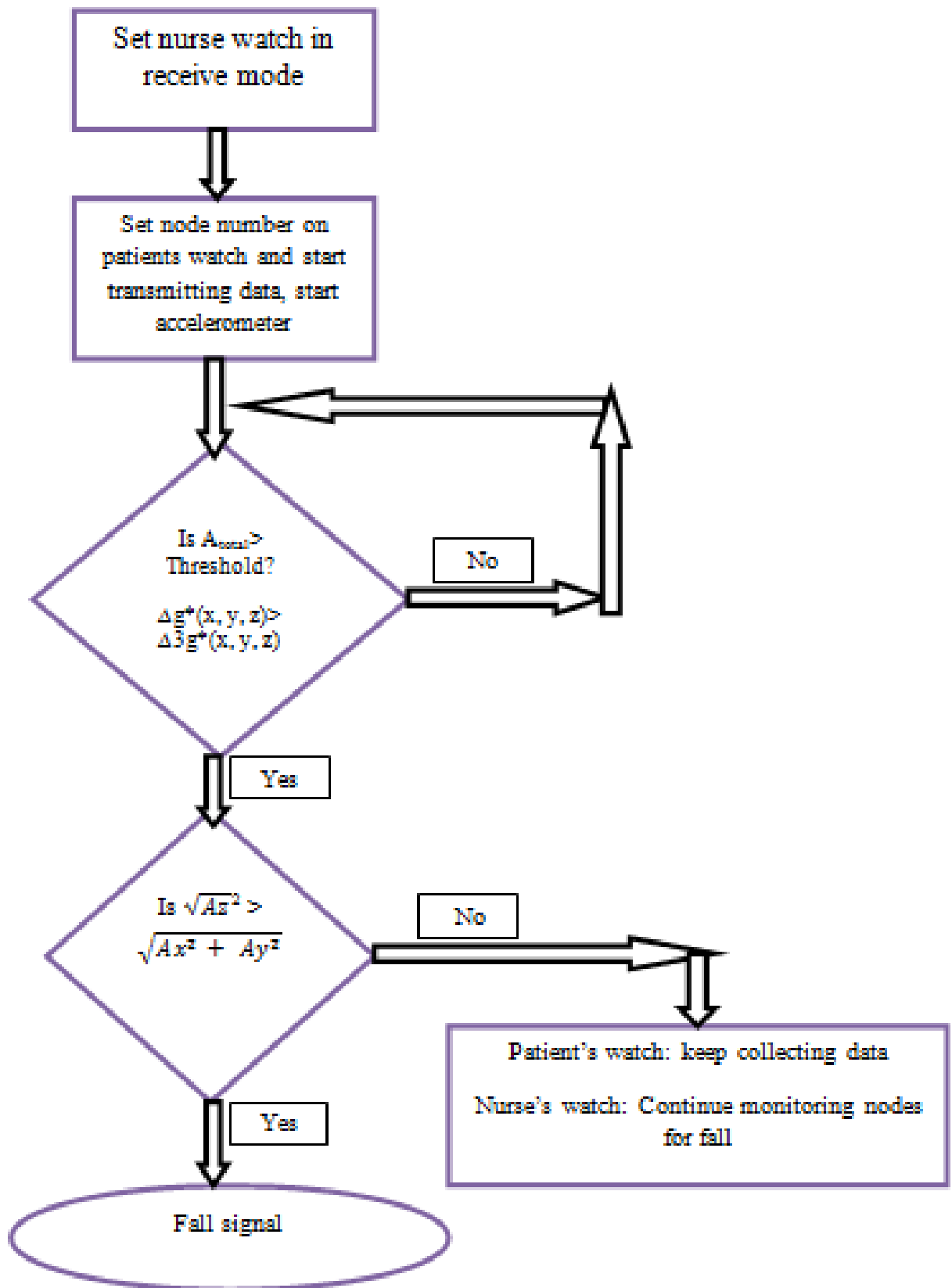


Figure 3.7: Fall detection algorithm

### 3.4. Working



**Figure 3.8: (a) Patient Watch in "Safe" mode (b) Nurse's watch waiting for the data**

Figure 3.8a shows “safe” mode on the display of the watch. This watch is worn by the patient and is programmed to be node one. Since it is meant to detect fall signals it is always in the transmit mode. When the patient is in a stationery position or when fall has not occurred the watch will always display “Safe”. Figure 3.8b shows the watch of the nurse. This watch is used for the purpose of monitoring transmitter nodes and waiting for fall signal. Therefore, the watch displays “Data Wait”. As long as the patient remains in stationery position and doesn’t fall, the watch will continue to wait for the data.

At this time, the display, the accelerometer and the antenna are the active components of the watch. It is made sure that other features are turned off to save battery power. The power consumed in the radio Transmission and reception mode is highest and may drain the battery.



**Figure 3.9: Fall signal on the patient's watch -programmed as node 1, Data being received on the display of nurse watch showing node 1.**

After a patient falls, the display on the watch changes from “safe” to “fall”. This is shown in Figure 3.9. This signal is immediately transmitted to the nearest receptor node. Thus, the display on the receiver watches changes from “data wait” to “data rx 01” 01 is the node number representing the fallen patient. This helps in identifying the fallen patient and sending him timely help. After the nurse reaches the patient who fell, his/ her watch must be turned off or set to idle mode to stop transmission and avoid the signal to reach other receiver nodes. Setting the watch in idle state also saves the battery and energy consumption.

Sometimes, a rigorous activity may also trigger a false alarm. This happens due to the overlapping ranges of acceleration. In case of a false alarm, the patient can stop the transmission and set the watch again into safe mode. Also, a fall signal may not be detected sometimes. In this case too, the patient has the option of manually setting alerting the authority to notify that he/ she fell. To avoid the false triggering, a buffer period of 1 to 2 seconds is required for the accelerometer to come back to its normal functioning after recovering from a sudden shock or a jolt.

### 3.5.Extended Research

Along with Texas Instruments' Chronos Module, Freescale Zstar3 device and FRDM board may also be used for fall detection. Having studied both the modules, the fall detection algorithm will be easier to implement in the Zstar3 module but programming it would become extremely difficult. The Zstar3 module comes with a tri-axial accelerometer sensor, 8bit micro-controller, 2.4GHZ transceiver and uses Zigbee protocol for communication purpose.



**Figure 3.10: Freescale's Zstar 3 device**

Zstar3 module is capable of having 16 nodes sensors in a star topology with a single base station controller unit. The controller unit is the computer running the Freescale application which monitors all the 16 nodes for fall detection. It offers flexibility to change the sampling frequency. Like the TI Chronos watch, even Zstar3 requires a 3V battery for operation. The range of communication ranges from 2m. Along with fall detection, it also has ability to detect taps and recognize gestures.



**Figure 3.11: Freescale's FRDM board**

Freescale's FRDM board consists of an 8 bit ARM Cortex micro-controller which has made it widely popular. It comes with a tri-color LED, tri0axial accelerometer and 16 I/O pins for further extension and development. A capacitive touch slider adds the feature of touch and tap recognition. Open SDA debug interface eases programming. External boards such Mbed or Arduino shield needs to be interfaced with the board for establishing wireless communication. Interfacing the board with a wireless USB device may solve the problem but may give rise to power issues. FRDM board is ultra low power and low cost development board. Successful implementation of the algorithm on it will not only save power but also reduce cost and introduce a very sophisticated product in market.

## Chapter 4 Energy and Power Analysis

TI Chronos eZ430 development kit is a low power SoC. In the CPU active mode, the current consumption is 160uA/MHz. In the radio RF reception/transmission mode at a frequency of 915MHz, the figure goes upto 15mA at a data rate of 250kbps.

The kit uses a Lithium battery of 3Volt for functioning. The estimated battery life for continuous acceleration measurement is one and a half months with average current of 166 uA. When in transmission mode, the battery life reduces to 2 days with current of 3.7 mA. Due to the very high current consumption during the transmission and reception of RF signals, the buzzer of the watch cannot be made to function on reception of the alert signal. This drains the battery completely and the display of the watch goes blank. Therefore, the watch needs frequent human monitoring.

$$\text{Power} = \text{Current} * \text{Voltage} \quad 4.7$$

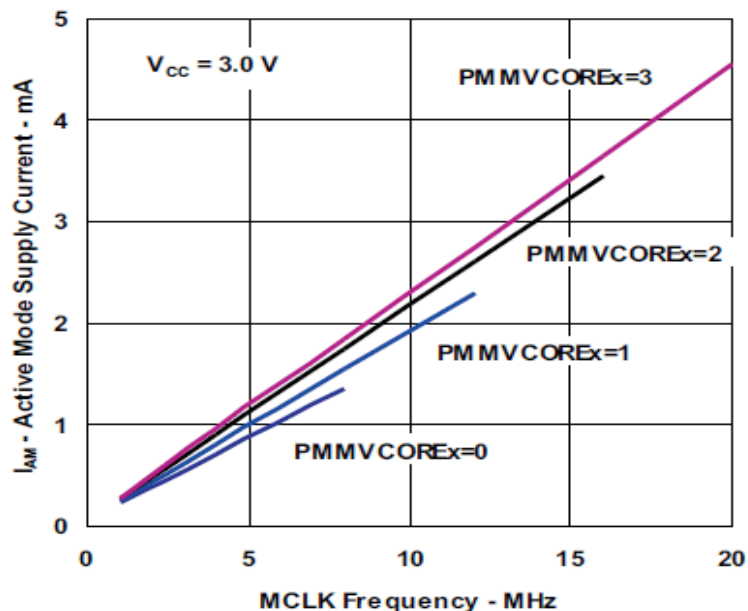
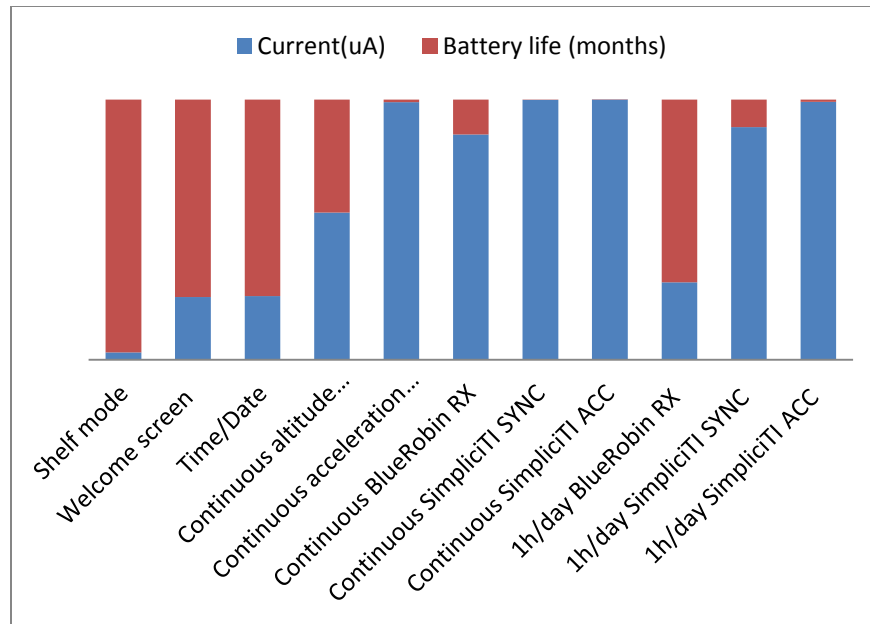


Figure 4.1: Current versus frequency values for the micro-controller in the watch





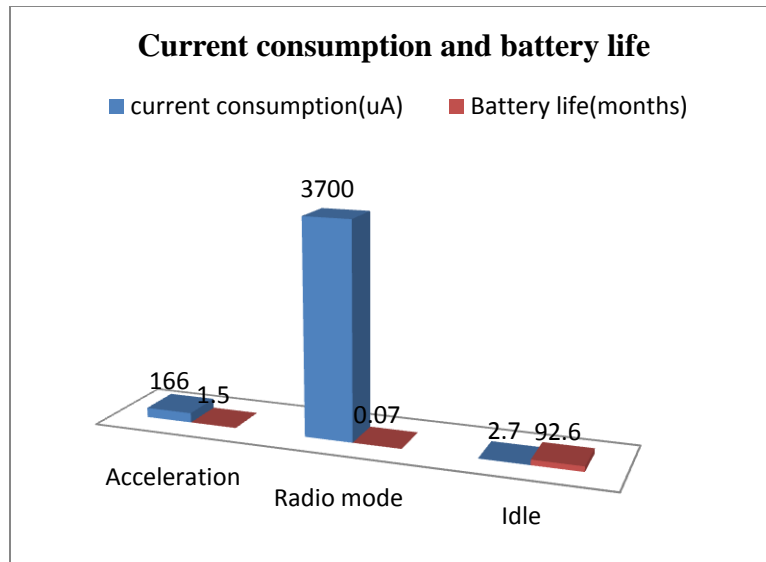
**Figure 4.2: Current consumption and battery life for different modes of eZ430 Chronos watch**

Figure 4.2 shows the current consumption and battery life for different mode of operation. eZ430 Chronos watch may be programmed for all the above modes, however, in this research only 3 modes are used. Comparison between the current consumption and battery life for these modes is shown in Figure 4.3.

Mode of Operation	Current (uA)	Battery life (months)
Shelf mode	2.7	92.6
Welcome screen	8.9	28
Time/Date	9	27.7
Continuous altitude measurement	18	13.8
Continuous acceleration measurement	166	1.5
Continuous BlueRobin RX	40	6.2
Continuous SimpliciTI SYNC	900	0.26
Continuous SimpliciTI ACC	3700	0.07
1h/day BlueRobin RX	10.3	24.2
1h/day SimpliciTI SYNC	46.1	5.4
1h/day SimpliciTI ACC	169.9	1.4

**Table 2 Mode of operation, current consumption and corresponding battery life**



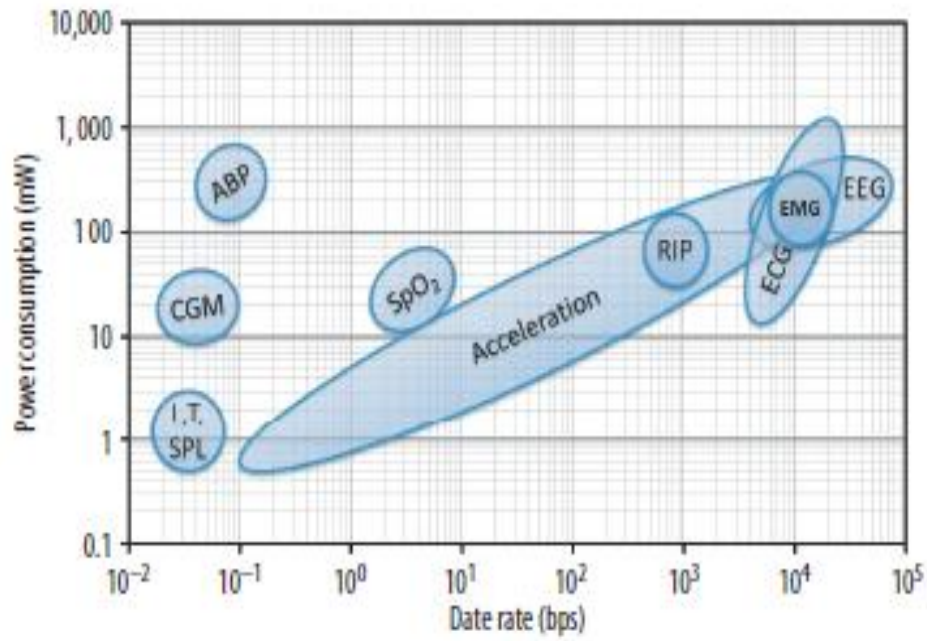


**Figure 4.3: Current consumption and battery life for 3 modes in the programmed watch**

Mode of operation	Current (uA)	Battery Life (months)
Acceleration	166	1.5
Radio mode	3700	0.07
Idle	2.7	92.6

**Table 3: Mode of operation and corresponding current consumption and battery life for programmed watches**

Table 3. shows the battery life and current consumption for the modes of operation implemented in this research. The watch is programmed only to function in the above three modes to save energy. Radio mode has the highest energy consumption due transmission and reception of data at a very high frequency of 915MHz. Along with the transmission; the watch module has an active accelerometer and a functional display which add to the current consumption. All these factors account for a shorter battery life and faster energy drain. The least energy consuming mode is the “idle” mode where the accelerometer and the antenna are disabled. Overall energy consumption also increases if the number of intermediate nodes increases between the paths from source to destination.



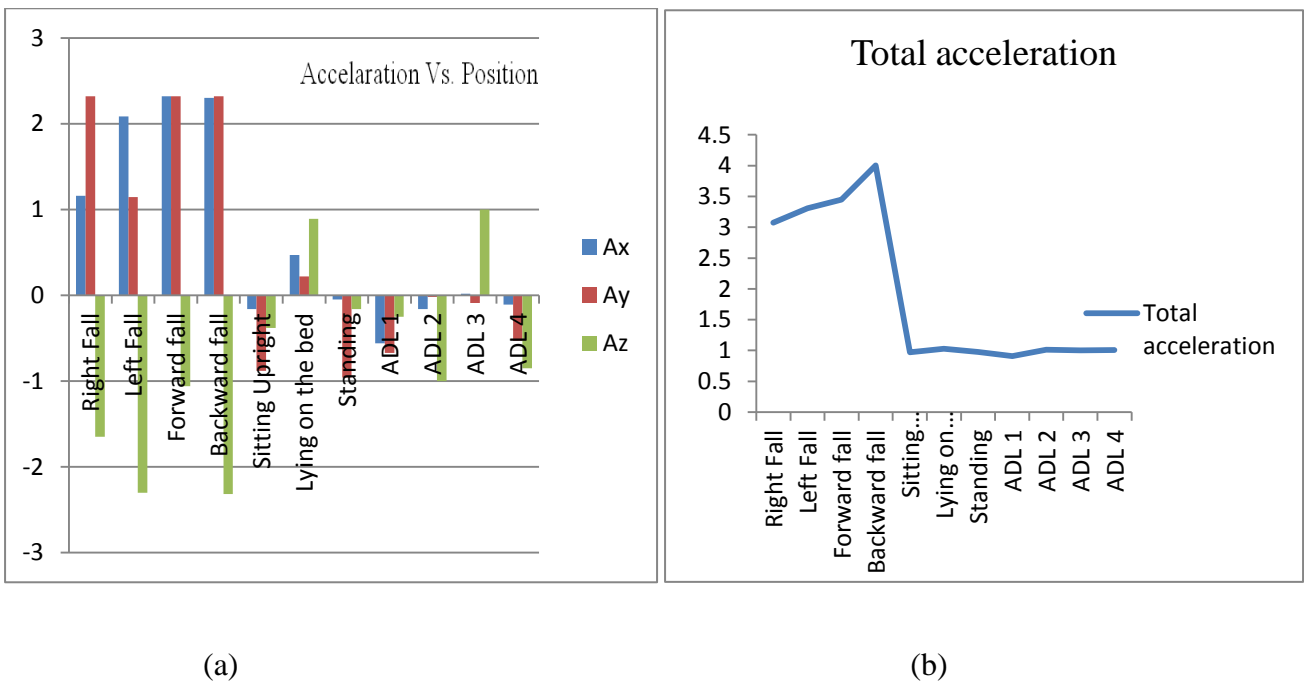
**Figure 4.4 Power consumption for monitoring ambulatory devices**

Figure 4.4 shows the power consumption in the ubiquitous monitoring systems used for medical applications. The most widespread data rate is found to be for accelerometer and the power consumed has an elliptical relationship with the amount of data monitored. This gives an idea about the significance of accelerometers in the medical field and also the power consumption characteristics for other devices used. These devices are used to measure ECG, EEG and CGM (Continuous Glucose Monitor) et al.

## Chapter 5 Results

The entire setup is capable of monitoring up to 9 sensors simultaneously. The number of patient nodes may be increased if required. This helps in forming a mesh network. Other factors like tilt, tap and free fall may also be measured using the accelerometer, sensor and the transceiver module. The sensor measures the x, y, and z co-ordinates and measures the change in acceleration due to gravity. The device software tool is also capable of plotting the change in co-ordinates on a scope window.

### 5.1.Acceleration



**Figure 5.1: (a)Changes in acceleration values for ADL and fall positions (b) Total acceleration for fall positions and ADL**

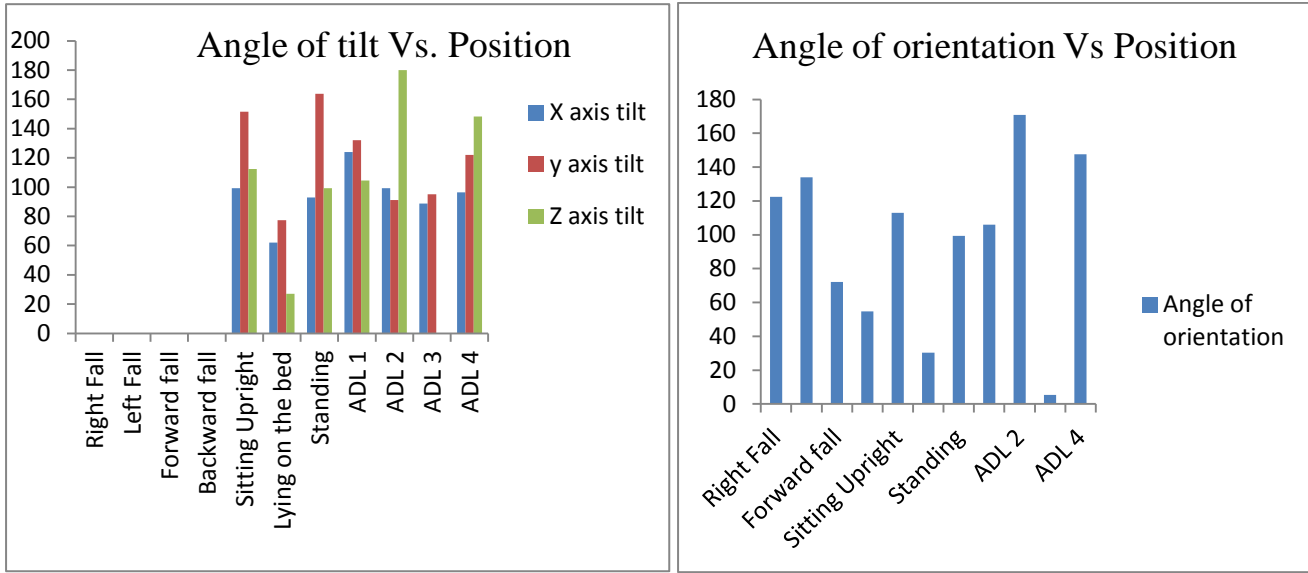
As mentioned earlier, acceleration plays the most important role in determining and distinguishing between a real fall and fall like activity. The graph above shows the difference in the acceleration values in 3 axes for fall and different ADL. Different positions and directions have been considered for fall. It is clearly seen that the bars on the left which represent fall activities are taller than the bars for fall like activities.

Body Position/fall	Total value of Acceleration-“g”times (m/s <sup>2</sup> )
Right Fall	3.071657433
Left Fall	3.307628141
Forward fall	3.44573145
Backward fall	<b>3.705086457</b>
Sitting Upright	0.971802449
Lying on the bed	1.03024269
Standing	0.974525526
ADL 1	0.908295106
ADL 2	1.012916581
ADL 3	1.004241007
ADL 4	1.007720199

**Table 4: Total acceleration for different fall position and ADL**

Table 4 estimates the total acceleration due to gravity for different fall scenarios and activities of daily life. It can be observed that the values of acceleration are extremely high for all the fall scenarios as compared to normal activities. The values are found to be three times the actual gravitational pull whereas, for routine activities the acceleration remains around the 1 g limit. For all ADL, the “g” value revolves around its real value because there is no sudden change either in the angle of bending or acceleration components in the x, y and z axes. It can also be seen that the highest range of “g” is four times its original value. This is the most critical and severe case of fall i.e. Backward fall. The analysis and approximations in the above table makes it easy to understand the difference in a fall and a fall-like activity in terms of mathematical calculations.

## 5.2.Angle of Orientation and Angle of Tilt



**Figure 5.2: Angle of tilt in different axes for fall positions and ADL**

Above graph gives the total acceleration for body fall and ADL. It is observed that the acceleration values for fall, especially backward fall is higher than the daily activities. Figure 4.2 gives a comparison between the position and the angle of tilt. It is observed that the angle of tilt is null for all the fall positions as the angle exceeds the threshold, whereas for ADL the angle remains within the threshold value.

Activity	Angle of Tilt for static bodies		
	X	Y	Z
Right Fall	-	-	-
Left Fall	-	-	-
Forward fall	-	-	-
Backward fall	-	-	-
Sitting Upright	99.20689622	151.642363	112.3336827
Lying on the bed	61.96570347	77.290967	27.12675312
Standing	92.86598398	163.739795	99.20689622
ADL 1	124.0557977	132.067065	104.4775122
ADL 2	99.20689622	91.145992	180
ADL 3	88.854008	95.1636071	0
ADL 4	96.31531557	122.005455	148.2116694

**Table 5 Angle of Tilt for fall positions and ADL**

Table 5 gives a comparative analysis between fall scenarios and ADL in terms of the angle of tilt. Angle of Tilt cannot be measured for any of the falls as the change in angle is so rapid that the reference normal which forms an angle with the acceleration normal may have more than one component together. This makes it extremely difficult to analyze tilt angles for falls. Therefore the columns for the x, y and z components have been left blank. Tilt-angle played a vital role in distinguishing static postures: lying, sitting and standing, as well as, the transitions between these static postures. However, in order to have an accurate estimate for the tilt-angle from the tri-axial activity acceleration-signals, accelerometer needs to be firmly attached to the human body. Loosely placing the sensor on the human body could result in changes in sensor's orientation while subjects perform a dynamic activity and, thus, makes it very difficult to land on a correct estimate for the tilt-angle. Therefore, tilt-angle was excluded from the feature-list in the case of accelerometer's position and attachment free recognition. Consequently, the three static postures: sitting, standing and lying, were combined into a single class called the resting-activity. Moreover, transitions between different activities were also not included in this study.

### **5.3.Sensitivity and Specificity**

The algorithm needed statistical analysis and result activity base on series of tests performed. There are 4 possible situations:

- True positive (TP): a fall occurs and the device detects it.
- False positive (FP): the device announces a fall, but it did not occur.
- True negative (TN): a normal (no fall) movement is performed, the device does not declare a fall.
- False Negative (FN): a fall occurs but the device does not detect it.

In [16], it was also proposed a classification and evaluation of fall detectors. Two criteria were proposed to evaluate the response to these four situations. Sensitivity is the capacity to detect a fall, eq 5.1 and specificity is the ability to detect only a fall, Eq. (5.2) [16]

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad 5.1$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad 5.2$$

Results show that the sensitivity of algorithm to distinguish between a real and false fall is 78% and specificity was found to be 69.2%. The rate of detecting false alarms was higher when the person moved wrist from higher to lower level with a free-fall like motion. Series of tests performed gave the following results in terms of success and failure percentage.

Scenario	Wrist		Waist/trunk	
	Success %	Failure %	Success %	Failure %
Falls	81	17	89	11
Non-Falls	73	27	88	12

**Table 5 Success and failure rate for fall detection.**

#### 5.4.Comparison with Present Algorithms

Implemented algorithm has several benefits over the ubiquitous algorithms in terms of design approach, privacy protection, reliability, fall detection, its success rate and energy consumption. As mentioned in [1]. Their experimental results show that the average accuracy rate for falls is around 95%. As compared to the presented algorithm which has an accuracy of 81%. However, the algorithm uses a one-to-one system i.e. every patient monitoring device is monitored by its corresponding terminal unlike in the presented algorithm where a number of patients may be monitored using one single device. Therefore, the scalability of algorithm is higher. Also seen in [2], [18] algorithm uses a truncated multiplier to set the threshold limits. This makes the algorithm extremely complex in terms of computations as it involves filtering data, multiplication and squaring. The complexity of the algorithm

designed and implemented in this research process the data at real time and the computations are quick too. Although the accuracy of the design in [2] is near 100% which is better than the presented algorithm. Also the power saved is higher as the system does not use battery powered monitoring devices. It can be said the algorithm presented in this thesis is more reliable than other algorithm mentioned above. Considering the change in reference co-ordinate points, calculating the Az component of acceleration along with total acceleration makes it extremely valid and accurate. Not only does the algorithm successfully differentiate between jolts, quick activities or sudden rigorous activity from a real fall but also prevents false alarm triggering. The algorithm protects the privacy of the patient as there is no video device employed for the algorithm implementation and detection of fall. It gives 100% privacy to the person. The wrist watch makes it comfortable for the patient to wear the device as compared to wear or implant it on waist. The following table gives the comparison results.

<b>Parameters of comparison</b>	<b>Presented algorithm</b>	<b>Compared algorithm 1 [21]</b>	<b>Compared algorithm 2 [22]</b>
Position of the device	Wrist	Waist	Chest
Privacy	Total privacy protection, video devices not employed	Privacy invaded due to presence of video monitoring cameras	Privacy remains intact
Threshold parameter	Change in reference co-ordinates, total acceleration, change of acceleration in Z axes, Angle of tilt	Change in human posture	Change in acceleration
Method of communication	Wireless transmission at 915MHz	Data transferred to computer from wired camera module	Bluetooth
Alarm triggering	Automatic alarm triggering	Automatic alarm triggering absent	Automatic alarm triggering absent
Reliability	Extremely reliable, avoids false triggering, differentiates between fall and fall-like activities, more reliable due to multiple thresholds	No differentiation between ADL and real fall. Less reliable	Side falls not detected, differentiates between ADL and fall
Power	100uW-1mW	Not considered	Not considered
Accuracy	81%	90%	96%
Range of communication	2-5 meters	Depends on lens' focal length	2 meters

**Table 6 Comparison with other designs**



Table 6 shows the comparison of the presented algorithm with other 2 designs. It can be seen that the implemented algorithm considers 2 threshold limits which makes it extremely reliable. The use of Chronos watch makes it very comfortable to wear. Also, alarm triggering is automatic which works well if the fallen patient goes in to and unconscious state. The algorithm takes in into account the energy and power consumption and makes efforts to mitigate the losses. Power analysis has not been presented by the compared algorithms. The fall detection mechanism makes sure to guard the privacy of the patient by not employing video devices for monitoring. The communication between the watches is secure i.e it prevents interception from other wireless devices and avoids false alarm triggering.

## Chapter 6 Conclusion and Future Improvements

This research aimed at developing a portable, compact and a wearable device for detecting human falls. The research has achieved its specified goal of differentiating between fall and non fall gestures and the setup successfully detects body fall. The wireless sensor networks helps in adding the feature of automatic, hand free assistance calling. It is also observed that the algorithm is 81% efficient when the watch is worn on the wrist. However, if the SoC is placed on waist or trunk of the patient, the efficiency increases to 89%. Since the TI Chronos kit is low power SoC, it consumes very little power and has an option of setting the watch in idle mode to save power.

Process flow of detection algorithm designed, it is small-size and more comfortable. The data is processed at real time and data processing is performed using micro-controller circuitry. Each sensor node processes the data and therefore, the fall-detection terminal is capable for independent work, and detects falls timely. The algorithm of fall detection is low-complexity and effective. The posture detection included most ADL events, except lying down in horizontal. Some falls were undetected, because of the factors of range overlap and buffer time for accelerometer restart. The experiments were not performed on the elderly and hence results may vary from the ones that are presented here. All tests were taken by young volunteers and fall were performed on mattress and not ground to ensure the safety of the volunteers. Through analysis of the kinetics characteristics of fall events, an effective method using a tri-axes accelerometer was proposed for automatic fall detection.

There are plenty features which can be included to improve the current setup. Also, false triggering of alarms due to overlap of range can be taken care by introducing another parameter like altitude. Change in altitude will help in giving perfect results. Altitude is an important criterion which may be considered to enhance the accuracy of the overall algorithm. In order to increase the range of the device, power amplifiers may be used in the path between the transmitter and the receiver node. Also, utilizing a higher voltage

battery may clear away the constant human monitoring by implementing application to trigger a buzzer or call an emergency phone. Further research and implementation of the above features will result in a fully functional product for nursing homes and hospitals of fall detection system which will be reliable and transmit data over the wireless mesh network and mitigate falls completely.

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